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Abstract

Electricity demand traditionally exhibits a substantial peak during a small number of hours each day. Policymakers are aware of the potential efficiency savings that may be generated from a shift in energy consumption away from peak times. Smart meters, in conjunction with time-of-use (TOU) pricing, can facilitate an improvement in energy efficiency by providing consumers with enhanced information about electricity consumption and costs, and thereby encourage a shift away from consumption during peak hours. In 2009-10, the Irish Commission for Energy Regulation (CER) co-ordinated a randomised controlled trial in the Irish residential electricity market. Smart meters, which replaced the existing mechanical meter readers, were introduced in approximately 5,000 households. Participants were divided into control and treatment groups, with treatment groups exposed to a variety of TOU tariffs and information stimuli (in-home display (IHD) units, monthly billing, *etc.*). Data was collected over approximately 18 months, with the first half year being used as a control period. This paper analyses the response of Irish households to the introduction of TOU tariffs and information stimuli. We examine how households responded to the different TOU tariffs, at different times of the day (peak, day and night) and in conjunction with different information stimuli. Finally, we examine the variation in our results across households of differing socio-economic status (as proxied by education levels). We find that TOU tariffs and information stimuli have a significant effect in reducing electricity consumption in Ireland, particularly during peak hours. However, while households reduce peak demand significantly after the introduction of TOU tariffs and associated information, there is little incremental response to increasing differentials between peak and off-peak prices.

JEL codes: Q41, D12

Keywords: household electricity demand, electricity pricing, smart metering

1 Introduction

Electricity demand traditionally exhibits a substantial peak during a small number of hours each day. Policymakers are aware of the potential efficiency savings that may be generated from a shift in energy consumption away from peak times. Smart meters, in conjunction with time-of-use (TOU) pricing, can facilitate an improvement in energy efficiency by providing consumers with enhanced information about electricity consumption and costs, and thereby encourage a shift away from consumption during peak hours.

In the EU, a number of recent pieces of legislation have promoted the use of smart metering, including the Electricity Directive 2009/72/EC, which requires Member States to ensure the implementation of intelligent metering systems and to carry out a cost-benefit analysis of the system by September 2012 (Commission for Energy Regulation, 2011b). In Ireland in May 2009 the first National Energy Efficiency Action Plan (NEEAP) was adopted in line with EU requirements, and included a commitment to encourage more energy efficient behaviour by households through the introduction of smart meters (Commission for Energy Regulation, 2011a).

In 2007, the Irish Commission for Energy Regulation (CER) announced their intention to introduce a trial smart metering experiment in the Irish residential and small-to-medium enterprise (SME) electricity markets.[1] Smart meters, which replaced the existing mechanical meter readers, were introduced in approximately 5,000 households and 650 SMEs. Participants were divided into control and treatment groups, with treatment groups exposed to a variety of time-of-use (TOU) tariffs and information stimuli (in-home display (IHD) units, monthly billing, *etc*.). Data was collected over the period 14 July 2009 to 31 December 2010, and as the experiment began on 1 January 2010, six months of pre-trial data are available for both the control and treatment groups.

Numerous other countries have experimented with the use of smart meters (e.g US, Canada and Denmark)[2], and there is a growing international literature analysing the impact of TOU tariffs on residential and commercial electricity consumption. The availability of high-quality data on a large and representative sample allows us to estimate the impact of TOU pricing on electricity consumption in Ireland for the first time.[3] Ireland is an interesting case study as much of the international literature focuses on the US where the use of air conditioning for residential use is common. As in Ireland there is no demand of air conditioning during the summer, the trial results show the impact of different TOU and stimuli on residential electricity demand net of the air conditioning effects, which accounts for a large part of the household responses in the US (Faruqui and Sergici, 2009). In addition, the data also allow us to investigate the impact of a variety of

[1] There were three distinct strands to the work; technology trials, customer behaviour trials and a cost-benefit analysis for the national roll-out of smart meters (Commission for Energy Regulation, 2011a).

[2] See www.ontario-hydro.com/index.php?page=current_rates and www.ctenergyinfo.com/dpuc_time_of_day_rates.htm [last accessed 01 September 2011] for example. Darby (2006) maintain that TOU pricing is most common in parts of the world with summer and winter peaks allied with supply constraints: California, Ontario, the north eastern states of the US and parts of Australia. For evidence on Denmark see Gleerup *et al.* (2010).

[3] While Gans *et al.* (2011) analyse the impact of enhanced feedback on electricity consumption in Northern Ireland, they focus just on a group of households who were already cognisant of their electricity consumption due to their choice of the prepayment option of payment. The extent to which their results are generalisable to other household types is debateable.

information stimuli on electricity consumption. Finally, limited socio-economic information on the participating households is also available.[4]

The first aim of this paper is therefore to disentangle the effects of the different TOU tariffs (peak, day and night) on residential electricity[5] consumption during different times of the day. Our results show that different information stimuli lead to differences in household responses during different times of the day. In particular, the presence of an IHD that indicates the quantity and cost of electricity consumed on a real-time basis leads households to contract their consumption during the peak hours, and the magnitude of the contraction increases as the ratio of peak to off-peak prices increases. However, the extent of the additional reduction in peak demand due to a steepening tariff schedule is very small in absolute terms. The other stimuli (i.e., bi-monthly and monthly paper billing) also give rise to reductions in peak demand when TOU tariffs are employed, but for them there is little evidence of further reductions as the ratio of peak to off-peak prices rises further.

Second, we investigate the determinants of electricity consumption during different times of the day. We find that controlling for day of the week, public holidays, climatic conditions and household appliance ownership, the presence of different TOU tariffs affects household electricity consumption during the peak hours, but does not lead to a significant change in electricity usage during the day and night periods.

Finally, we examine the variation in our results across different socio-economic groups, as proxied by the highest level of education completed by the chief income earner of the household. We find that households with higher education levels respond to TOU tariffs during the peak period (consistent with the overall results noted above), but that households with low education levels are less responsive to TOU tariffs.

Section 2 discusses previous research in the area. Section 3 describes our data, while Section 4 outlines the methodology employed in this paper. Section 5 presents and discusses empirical results, while Section 6 summarises and concludes.

2 Literature review

Estimates of the price elasticity of electricity demand in the residential sector can be very different depending on the type of data used (time-series, cross-section, panel), context (national, regional or local economy), size of the variation in price and time periods covered (see also Alberini *et al.*, 2011). Here we focus on studies that, similar to the approach used in this paper, use micro-data on households and that examine the impact of price and information stimuli on electricity demand.

[4] As described in Section 3, the quality of the data relating to household income was poor, and as a result, the education level of the chief income earner is used to indicate household socio-economic status.
[5] As explained in Section 3, we concentrate on residential customers only in this paper.

The extent to which price elasticities differ across population groups is a common focus of research in this area. Baker *et al*. (1989) use data from the British Family Expenditure Survey over the period 1972-1983 to analyse household expenditure on electricity, gas and other fuels. Prices are national averages. They find a significant own-price elasticity of -0.758 for electricity demand, with considerable variation in the estimated own-price elasticity across different household types (e.g., by presence of children, type of heating, income, *etc.*). Alberini *et al*. (2011) estimate price elasticities of energy (electricity and gas) demand using data on over 74,000 households in the 50 largest metropolitan areas in the US over the period 1997-2007. They report price elasticities of demand for electricity use that range from -0.67 to -0.86, with the elasticities slightly higher in poorer households.

As TOU pricing is becoming more common, so too are studies evaluating households' responses to TOU pricing. Bartusch *et al*. (2011) examine the impact of the introduction of a demand-based TOU tariff on a pilot basis to a group of 500 households in Sweden. Using data before and after the introduction of the TOU tariff, they find that total electricity consumption declined by 11.1 per cent and 14.2 per cent in the first two years after the change to TOU pricing (with the size of the reductions higher in the winter months). They also find a shift in electricity demand from the peak to off-peak period of 0.8 and 1.2 percentage points in the first two years (with the shift greater during the summer months). Filippini (2011) analyse electricity data at the city level for 22 Swiss cities over the period 2000 to 2006. They find that the own-price elasticities vary between -0.80 and -0.89 during the peak period and between -0.90 and -0.95 during the off-peak period (positive cross-price elasticities imply that peak and off-peak electricity are substitutes). An earlier study, also using Swiss data, found similar results (Filippini, 1995). Matsukawa (2001) examine the impact of TOU pricing on residential electricity demand in Japan. The results show that (1) household response to the high price of the peak period is relatively modest, and (2) the relative magnitudes of the price and selection effects (i.e., participation in the trial) depend on the ownership of water heaters.

Ham *et al*. (1997) discuss the importance of accounting for selection when using experimental data (the bias induced by voluntary participation in such initiatives is also discussed by Aubin *et al*., 1995). They measure the responsiveness of small commercial customers to TOU pricing using data from a TOU experiment conducted by Ontario Hydro. Participants were randomly assigned to control and treatment groups, but approximately half of the treatment group refused to participate. Allowing for selection has a significant impact on the parameter estimates. Nonetheless, they find a significant reduction of 15 per cent in electricity consumption when the peak period is relatively short in length (approximately 5 hours) and the peak/off-peak price differential is approximately six to one. For the other two treatments, where the length of the peak period is longer and the price differential is smaller, no significant reduction is observed. Own-price elasticities of demand are estimated to be -0.134 in the winter and -0.114 in the summer.

A variant on TOU pricing is dynamic pricing, whereby rates respond to critical periods of electricity use. In the US, critical periods occur typically during the top one percent of the hours of the year where somewhere between 9-17 percent of the annual peak demand is concentrated. It is very expensive to serve power during these critical periods and even a modest reduction in demand can be very cost-effective (Faruqui and Sergici, 2009). A comprehensive review of 15 experiments (largely based in the US)[6] with dynamic pricing of electricity was undertaken by Faruqui and Sergici (2009). They find conclusive evidence that households (residential customers) respond to higher prices by lowering use. The magnitude of the price response depends on several factors, such as the magnitude of the price increase, the presence of central air conditioning and the availability of enabling technologies such as two-way programmable communicating thermostats. Across the experiments studied, TOU pricing induces a drop in peak demand that ranges between three to six percent and critical-peak pricing tariffs induce a drop in peak demand that ranges between 13 to 20 percent. When accompanied with enabling technologies, the latter set of tariffs lead to a drop in peak demand in the 27 to 44 percent range. Wolak (2011) examines whether households in Washington DC face a 'fixed cost of taking action' when responding to dynamic hourly prices; he finds that the magnitude of the average hourly percentage demand reduction from hourly pricing is roughly equal to the estimated percentage demand reduction over a longer duration of high prices.

Charles River Associates (2005) examine the impact of the California Statewide Pricing Pilot (SPP) on residential and industrial electricity demand (a TOU and two dynamic pricing tariffs were tested). The experiment involved over 2,500 customers and ran from July 2003 to December 2004. The SPP also tested an information treatment that urged customers to reduce demand on critical days in the absence of time-varying price signals. For residential customers, the estimated average reduction in peak-period energy use on critical days was 13.1 percent. Impacts varied across climate zones, from a low of –7.6 percent in the relatively mild climate of zone 1 to a high of –15.8 percent in the hot climate of zone 4. The average impact on normal weekdays was -4.7 percent, with a range across climate zones from –2.2 percent to –6.5 percent. They also found that households with central air conditioning were more price responsive and produced greater absolute and percentage reductions in peak-period energy use than did households without air conditioning. TOU impacts were less significant, due in part to the small sample size, while the information-only treatments were similarly insignificant.

As in our experiment, TOU pricing is often combined with various information stimuli. Darby (2006) reviews the literature on the impact of feedback (both direct in the form of meters or display monitors, and indirect in the form of frequent, accurate billing) on household energy use. She finds that overall the literature demonstrates that clear feedback is a necessary element in learning how to control fuel use more effectively over a long period of time and instantaneous direct feedback in combination with frequent, accurate billing (a form of indirect feedback) is needed as a basis for sustained demand reduction. There is some indication that high energy users may respond more than low users to direct feedback. In terms of indirect feedback, historic feedback (comparing with previous recorded periods of consumption) appears to be more effective than comparative or normative information (comparing with other households, or with a target figure).

[6] All experiments are based on panel data, involving repeated measurements on a cross-section of customers. Some of the customers are placed on the dynamic pricing rate (or rates) and fall into the treatment group. Others stay on existing rates and fall into the control group. Technically, the control group should be randomly chosen (Faruqui and Sergici, 2009).

Gans *et al*. (2011) estimate the effect of real-time usage information on residential electricity consumption in Northern Ireland. They exploit the introduction in an exogenous change in the type of information provided to one set of customers, i.e., those on prepayment accounts, in April 2002. From that date, prepayment customers received immediate feedback about their electricity consumption via keypad meters.[7] They use data from 18 waves of Continuous Household Survey of Northern Ireland (from 1990 to 2009), which is merged with price and plan information from the electricity utility, and weather data (the final sample size is over 45,000 observations). They find that households using the keypad use 15-20 per cent less electricity than other households, even controlling for housing type, heating, household characteristics and selection into the plan. Their estimated own-price and income elasticities are -0.72 and 0.04 respectively. Also in Ireland, Dulleck *et al*. (2004) use monthly time-series data of household electricity use over the period 1976 to 1993 to examine the impact of demand management policies that provided information and offered minor incentives to customers (e.g., information leaflets with households' electricity bills). They find that the introduction of information programs reduces long-term electricity usage by 7 per cent.

In a statistical analysis of the Irish data to which we apply econometrics later in this paper, Commission for Energy Regulation (2011a) finds that application of TOU tariffs with a selection of informational stimuli reduce overall household electricity use by an average of 2.5 per cent and peak demand by 8.8 per cent. They also find that households with an IHD or with high pre-trial demand reduced demand more than others, but that increases in the ratio of peak to off-peak prices beyond the initial step tested do not lead to further statistically significant reductions in demand. They conclude that demand is highly price inelastic.

3 Data

The residential component of the trial involved over 5,000 households (customers of Electric Ireland[8]) who were asked to participate in the trial.[9] In order to assess whether TOU pricing and information stimuli led to a change in household electricity consumption, half-hourly data were collected for each household over the period 14 July 2009 to 31 December 2010.[10] Households were randomly assigned to either the control or treatment groups for the commencement of the experiment on 1 January 2010. The control group was billed on their normal tariff and saw no changes to their bill. They received none of the information stimuli and were requested to continue using their electricity as normal (Commission for Energy Regulation, 2011a). Benchmark pre-trial data is available for all households (both control and treatment) for the period 14 July 2009-31 December 2009.

[7] The keypad meters combine a rechargeable card control with an interactive display that allows consumers to easily monitor their electric usage and cost. In November 2010, they accounted for just over one-third of residential electricity customers.

[8] At the time of recruitment (mid-2008), Electric Ireland customers represented 100 per cent of residential electricity customers in Ireland (Commission for Energy Regulation, 2011a).

[9] We focus on residential electricity participants in this paper, as the publicly-released micro-data relate only to residential participants in the trial.

[10] Data collection started earlier in 2009, but the anonymised dataset provided to researchers omitted data collected up to 14 July due to incompleteness of the sample.

Treatment households were randomly assigned to different TOU tariff groups and to different information stimuli groups. The allocation of treatment households between tariffs and information stimulus groups was decided by the regulator at the end of 2009. In order to allocate the treated groups between different tariffs and information stimuli a principal component analysis was applied to identify the main household characteristics and to optimally combine interest in energy reduction and usage profile. Given these combinations, the participants were randomly allocated to different treatment groups.[11]

Four TOU tariffs were tested. TOU prices referred to peak (17:00-18:59 Monday-Friday, excluding public holidays), day (08:00-16:59; 19:00-22:59 Monday-Friday, plus 17:00-18:59 public holidays, Saturday and Sunday) and night (23:00-07:59) periods (based on system demand peaks). A weekend tariff was also tested (whereby the night rate applied all day Saturday and Sunday, with separate peak, day and night tariffs for weekdays). In comparison with the initial flat-rate tariff, the electricity price associated with peak hour consumption rose up to a maximum of 166 per cent of its initial value, while the price of electricity during the day and night was decreased by a maximum of 13 per cent and 37 per cent respectively. The TOU tariffs were designed to be neutral in comparison with the standard flat-rate tariff to ensure that the average participant who did not change their electricity consumption would not be financially penalised.

The regulation authority states that " *Throughout the Trial all participants testing time-of-use tariffs were guaranteed that they would not pay more for their electricity than if they had been on the normal Electric Ireland tariff (14.1c per unit ex VAT). Accordingly, all participants received a balancing credit at the end of the benchmark period and in January 2011. The small number of individuals who incurred costs above this average were recompensed on a case by case basis*".[12]

The base TOU tariff (Tariff A) reflects the underlying cost of energy transmission, distribution, generation and supply (Commission for Energy Regulation, 2011a). Table 1 sets out the various price levels applying in the control and treatment periods.[13]

[insert Table 1 here]

In addition, treatment groups were also subjected to one of four information stimuli.[14] In Ireland, electricity customers typically receive bi-monthly paper bills. Households in the treatment group were randomly assigned to one of four groups; bi-monthly billing, monthly billing, bi-monthly billing plus IHD stimulus, bi-monthly billing plus overall load reduction (OLR) stimulus. OLR refers to households who received €20 (plus their energy savings) if they reached a monthly target (based on

[11] For a complete description of the allocation between stimulus and tariff groups see Commission for Energy Regulation (2011a).

[12] These payments ranged from €30 under Tariff A to €90 under tariff D (Commission for Energy Regulation, 2011 a pp.8).

[13] There is some debate in the literature over whether households respond to average or marginal prices. It has been argued that households respond to average price, which is easily calculated and observable (see Alberini *et al.*, 2011 for example).

[14] Treatment households were also supplied with a fridge magnet (detailing the time bands and associated costs) and a sticker (detailing the time bands) (Commission for Energy Regulation, 2011a).

historic trend minus 10 per cent). As the precise prices faced by households in the OLR group could not be determined, we excluded these households (n=940) from our analysis.[15] Among the treatment group therefore, 13 distinct groups defined by combinations of the various TOU tariffs and information stimuli are identified. Table 2 outlines the numbers of control and treatment observations available for analysis.[16]

[insert Table 2 here]

The quality of the data on electricity consumption is very high. Only a small percentage of households were excluded due to incomplete records (i.e., due to signal problems impacting on the return of half-hourly smart meter readings). Detailed information on each of the participating households was also collected, both before and after the trial period. Information on household composition, appliance ownership and use, as well as attitudes towards energy conservation and the environment was collected. As detailed below, we also examine the response of different household types to the various TOU tariffs and information stimuli. This requires detailed information on household composition and socio-economic status. We use an indicator of the highest level of education completed by the chief income earner of the household in order to identify different household types as there are some problems with other potential indicators.[17]

As the control period started on the 14th of July 2009, we also exclude the first seven months of the treatment period to correctly estimate household responses to the introduction of tariffs and information stimuli. The final sample size is 967,756 observations, across 2,831 households (768 in the control group, and 2,063 in the treatment group).

The main focus of this paper is the estimation of the reaction of households to different TOU tariffs and different information stimuli. However, electricity demand is also affected by other factors. As discussed in Section 2, previous research has highlighted the importance of the weather and the number of appliances in each household in determining electricity consumption. In addition to price and information stimuli, we therefore include in our analysis the number of electric appliances owned by the household[18], and proxies for the temperature and climate variables in the form of heating degree days (HDD) and sunshine hours for each individual day over the period 14 July 2009 –

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[15] A sample of the information provided with the bills can be found on pp.85 of Commission for Energy Regulation (2011a).

[16] Half-hourly data were aggregated to daily totals.

[17] For example, the indicator of household income is poorly recorded (many missing observations, and an analysis of the summary statistics indicates that the wording of the question caused confusion among households in relation to whether responses should be annual, monthly or weekly income, or pre- or post-tax. In addition, information on the number and ages of individuals in the household did not allow us to distinguish among households with children of different ages.

[18] For the appliances we consider the numbers of washing machines, dishwashers, tumble dryers, laptops and PCs, TVs, electric cookers, electric showers and standalone freezers owned by each household. In the heating dummy variable we consider whether the household has electric heating or an electric water heating/pumping system in the house. The number of appliances is strongly significant in all our estimations.

31 December 2010.[19] We also include a categorical variable that indicate the day of the week, and a binary variable that indicates public holidays.

Moreover, we create a dummy variable which is equal to 1 for households that have electric heating, and we interact this variable with the HDD indicator, to control for heterogeneity in the response to temperature among households that have different heating methods. In this way, we also control for potential effects on electricity consumption during the months of November and December 2010, when it was unusually cold in Ireland (see Figure 1).

4 Methodology

The main advantage of the experiment conducted on smart metering and TOU pricing in Ireland is that our data are unaffected by the selection bias that usually characterises this type of analysis.[20] While initial participation in the experiment was not random, households were subsequently randomly assigned to either the control or treatment groups. This means the sample was collected with the objective that the treatment and the control groups should not have any significant differences apart from the treatment. In order to test the effectiveness of this approach, we estimated a probit model in which the dependent variable was the probability of being part of the treated group and the independent variables were household characteristics (age of the individual who responded to the household questionnaire, appliances used by the household, level of education of the chief income earner of the household). None of these variables proved to be significant at the standard significance levels, as highlighted in Table 3. Moreover, a comparison of the means of different variables that summarise the household characteristics did not show any significant difference. [21]

[insert Table 3 here]

As we also have information from the benchmark period for control and treatment groups, the natural choice of estimator for the reaction to different tariffs and stimuli is the difference-in-difference estimator. This technique allows us to correctly estimate the difference in the means between the control and the treatment groups in the treatment period, controlling for common trends across the two groups during the control period.

Let us denote μ_{it} as the mean of the outcome of the group *i* at time *t*, in which *i* is equal to 0 (control group) or 1 (treatment group) and *t* is equal to 0 (control period) or to 1 (treatment period). As the only difference between the households who populate our sample is the treatment, we estimate the difference-in-differences $(\mu_{11} - \mu_{01})$, using the random effects estimator for panel data.

[19] Information on HDD and sunshine hours is available for Dublin Airport only. In any case, more detailed information on the regional location of households is not available.
[20] See Card and Kruger , 1984), among others.
[21] Details on request from the authors.

We estimate three different versions of our model: a benchmark case; a model in which the sample is divided by the highest education level of the chief income earner of the household; and models in which we distinguish between additional household types (based on the age of the survey respondent, and the occupancy status of the household (rent, owned outright and owned with mortgage)).

Impact of different TOU tariffs on electricity demand

In order to test the impact of a change in the tariff structure, given the different information stimuli, we estimate the following equation:

$$\begin{aligned} q_{i,t} = \alpha_0 &+ \alpha_1 TariffA_{11} + \alpha_2 TariffB_{11} + \alpha_3 TariffC_{11} + \alpha_4 TariffD_{11} \\ &+ \alpha_5 TariffW_{11} + \alpha_6 D_{phol} + \sum_{i=1}^{6} \alpha_7\, Wkdays + \alpha_8 sunshine_t + \alpha_9 HDD_t \\ &+ \alpha_{10} T_t + \alpha_{11} T_g + \alpha_{12} Appliances + \alpha_{13} ElectHeat \\ &+ \alpha_{14} HDDElecHeat \end{aligned} \quad (1)$$

in which $q_{i,t}$ is the daily consumption of electricity in the three different time of the day (peak, day, night), $TariffA_{11}$ is the dummy variable indicating that the household was exposed to tariff A during the treatment period, $TariffB_{11}$ is the dummy variable indicating that the household was exposed to tariff B during the treatment period, etc. $TariffW_{11}$ is the dummy variable indicating that the household was exposed to the weekend tariff during the treatment period (this tariff was applied only to consumers facing the bi-monthly billing information stimulus). T_t is the dummy variable for the treatment period, T_g is the dummy variable for the treated group, D_{phol} is the dummy variable for public holidays, *Wkdays* are dummies which are equal to 1 on the various days of the week, *HDD* is a variable that reflects the heating degree days, *sunshine* is a variable that reflects sunshine hours (not included in the night specification), *Appliances* is a count variable of the number of appliances owned by the household and *ElecHeat* is a dummy variable indicating that the household has an electric heating system. The variable *HDDElecHeat* is a variable that interacts the HDD with the ElecHeat dummy; this variable should control for high electricity consumption during the winter of 2010, in which the temperatures in Ireland were exceptionally low, as well as the differential response to TOU tariffs among households with different heating types. The coefficients $\alpha_1 - \alpha_4$ represent our difference-in-difference estimates (i.e., the effect of the four TOU tariffs on household electricity consumption). We estimate nine different specifications of the model, which represent different combinations of time of day (peak, day, night) and information stimulus (bimonthly billing, monthly billing, IHD).

The treatment period dummy T_t that we include in our analysis simply indicates the differences in the dependent variable between the control and the treatment period, that is: $T_t = E(y_i|contrp) - E(y_i|treatmentp)$. We expect that this variable will be negative and significant in all models, as the change in tariffs and information stimuli should lead treated households to be more aware of their electricity consumption and to take steps to reduce their consumption. On the contrary, we expect that the treatment group dummy T_g will be always insignificant as the treatment and the control groups are not statistically different to each other (as demonstrated above).

Differential response to TOU pricing and information stimuli by household education level

To correctly disentangle the differences in electricity consumption between households with different socio-economic characteristics we re-estimate model (1) for different subsamples of the initial sample. The response rate to the income question in the pre-trial survey was poor, and the information on household composition (e.g., number and ages of children) is not detailed enough to construct a household composition variable. Instead, we use information on the highest education level of the chief income earner of the household. We disaggregate households on the basis of whether the chief income earner had a third level qualification or not (38.3 per cent of households are thus classified as ‘high education households’, while 61.7 percent are classified as ‘low education households’).

The education level of the household (proxied by that of the chief income earner) may have non-trivial effects on electricity consumption during different times of the day: on one hand, high education households may be more concerned about the efficient use of their appliances, and we therefore might observe a higher contraction in consumption during the peak hours among these households than among low education households. On the other hand, education can (at least partially) pick up some of the income effects, and so we might expect that low education households might be more concerned about price than the high education households.

Differential response to TOU pricing and information stimuli by alternative household characteristics

While the education level of the chief income earner is our main indicator of household socio-economic status, we also ran the models using alternative household sub-samples. First, we distinguish between households of different ages, as proxied by the age of the survey respondent. We consider 4 different age groups: young people, aged 18-34; adults aged 35-54; adults in the last stage of their career (55-64) and retired people (i.e., those aged 65+). Second, we also consider household occupancy status. While acting as a proxy for household resources, this potentially also affects the household reaction to different prices as the inclusion of utility payments in rent may reduce the effectiveness of increasing electricity prices.

5 Empirical Results[22]

Impact of different TOU tariffs on electricity demand

Tables 4-6 present the results of the difference-in-difference analysis of the introduction of TOU tariffs for the peak, day and night periods respectively (with the samples further disaggregated by information stimuli). The treatment period dummy is strongly negative and significant in both the peak and day specifications. The same result emerges from the analysis performed by Faruqui and Sergici (2009); however, our results are not directly comparable as their study accounts only for differences in the pricing structures before and after the treatment period, whereas our analysis also assesses the impact of differences in information stimuli. As expected, the consumption of electricity decreases more during peak than day hours. Moreover, in our analysis electricity consumption decreases even during the night hours, but this decline is not statistically significant. As expected, the treatment group dummy is always insignificant, with the exception of the night specification where it is sometimes weakly significant. [23]

Variables relating to the day of the week are largely significant, and have signs that are consistent with expectations (i.e., relative to Wednesdays, peak consumption is lower, and day consumption is higher on weekends). Peak period electricity consumption is also significantly lower on public holidays (and day consumption correspondingly higher).

The influence of the weather is highly significant. The effects of HDD and sunshine hours are positive and negative respectively.[24] When HDD is interacted with the indicator for electric heating, the effect of HDD is more strongly positive, indicating the particular burden that low temperatures place on those that rely on electric heating. Finally, the number of appliances installed in each house is positive and significant in all the different specifications of the model.

From Table 4 it is clear that consumption during the peak hours is negatively affected by the initial introduction of TOU tariffs. However, across the different information stimuli, there are differences in both the magnitude of the effects, and how consumption responds to increasing tariffs. For example, in the peak period model, electricity consumption is always lower under tariff D (with the

[22] For the smart metering experiment analysed in this paper, a statistical analysis of the impact of the TOU tariffs and information stimuli on total and peak demand was also carried out on behalf of the Commission for Energy Regulation by The Research Perspective and Insight Statistical Consulting (Commission for Energy Regulation, 2011a). They found that overall, the introduction of the TOU tariffs and the information stimuli resulted in statistically significant reductions in total electricity consumption of 2.5 per cent and peak electricity consumption of 8.8 per cent. These results were used subsequently in the cost-benefit analysis of the smart metering trial. They also found that the stimulus combining bi-monthly bill, energy usage statement and electricity monitor was more effective than other information stimuli in reducing peak usage with a peak shift of 11.3 per cent, and that households with higher electricity consumption were more responsive to TOU pricing and the information stimuli.

[23] For the night specification this dummy might include a compositional difference between the treatment and control groups that exists in the night time (and which was not apparent in the overall results presented in Table 3).

[24] We exclude the number of sunshine hours from the night demand analysis.

highest ratio of peak to night prices) than under tariff A (with the lowest). In the households where IHDs are installed, there is a linear relationship between the size of the tariff applied and the contraction in electricity consumption. However, when the stimulus is characterised by the provision of less frequent information (bi-monthly or monthly paper billing), the magnitude of the reduction is different across the different tariffs. For instance, when the households receive a bi-monthly bill, the contraction in electricity consumption during the peak is higher under tariff B than tariff A, which is plausible. However, households that face tariff C do not respond to the increase in the peak period electricity tariff, although those on tariff D do respond significantly. A similar nonlinearity in the consumption contraction in the peak period under the four different tariffs is associated with the monthly billing stimulus, although the pattern is closer to that observed for the IHD stimulus.

Although the IHD stimulus is associated with the most consistent-looking price response, it is still weak in absolute terms. The ratio of peak to night prices rises from about 1.7 in Tariff A to 4.2 in Tariff D as per Table 1. This is a substantial relative price change. Nevertheless, the associated reduction in peak usage is only 1 per cent for each step change in tariff and a total of 4.5 per cent from Tariff A to D. More than a doubling of the peak/night ratio leads to a reduction of less than 5 per cent in peak demand. These results show some consistency with previous research. Reiss and White (2005) found a non-linear reaction between the changes in electricity demand and the applied electricity prices in California. Pollitt and Shaorshadze (2011) and Ito (2010) discuss the possibility that the lack of continuous information might affect consumer reactions. Allcott and Mullainathan (2010) and Allcott (2011) highlight how consumers believes can be systematically biased when they are evaluating energy costs.

In the Irish experiment, monthly and bi-monthly billing might not provide sufficient information to households, who then cannot regulate their behaviour consistently with the tariff applied. In contrast, the provision of real-time information on both the quantity and cost of electricity consumed via the IHD seems to result in more consistent behaviour among the treatment group households (at least in the peak period). Overall, household responses may be dominated by application of some simple heuristic: they know peak prices are now higher than other times of day and they change behaviour to reflect this, but further increases in the differential are either not fully perceived or evoke only a weak response for some other reason.

Electricity consumption during the day and night is less responsive to TOU tariffs. As Table 1 highlights, the changes from the control period for the day tariff were quite low (ranging from -2.2 per cent under tariff A to -12.6 per cent under tariff D), so it is perhaps understandable that households did not change their consumption significantly.

In contrast, night tariffs varied from -16.1 per cent to -37.1 per cent than those applying in the control period. However, the lack of reaction of the households to TOU pricing in the night period under all the various stimuli may be explained by considering that consumers tend to react more to a price increase than to a price decrease (see Dawes, 2004). In addition, the night tariff began at 11 p.m, making it difficult to shift the usage of many appliances (cooker, shower and washing machine) to these hours.

Differential response to TOU pricing and information stimuli by household education level

To ascertain whether the response to TOU pricing is different across households with different education levels, we run the models on the subsamples of low education and high education households. Tables 7 and 8 present the results of the difference-in-difference analysis for the low- and high education households with IHDs respectively.[25]

[insert Tables 7 and 8 here]

Focussing on the peak period first, the results indicate that low education households respond only to higher peak prices when receiving a monthly bill, or in possession of an IHD. The reaction of high education households to the peak pricing structure is similar, although the effects are slightly smaller in magnitude, and there is some response to higher peak prices among high education households who receive a bi-monthly bill. This suggests once again that regular feedback in the form of an IHD is more effective in reducing peak-period electricity consumption than other stimuli, and the results also provide some evidence to suggest that this effect is stronger for low education households. As with the baseline results, day consumption is largely unaffected by TOU pricing. High education households are similarly unaffected by TOU pricing for night consumption, while TOU pricing has a significant effect on night consumption for low education households who have an IHD. The effects show that decreasing night prices are associated with increasing consumption, which suggest that low education households with an IHD are responding to TOU tariffs by shifting consumption to the night hours. There is no such effect for low education households with the bi-monthly or monthly billing options however.

Differential response to TOU pricing and information stimuli by alternative household characteristics

Splitting the sample using alternative indicators of household socio-economic status confirms the general results. However, some interesting conclusions might be drawn for the age groups and the house occupancy type. First, adults (aged 35-54) are the most responsive to changes in the peak prices, when IHD is installed. Second, households who are renting their apartment seem to be less responsive to change in peak pricing than households who live in their own houses. The last result can be understood by considering that sometime the rent is inclusive of the utility bills; this affects the incentives in changing the electricity consumption in presence of different tariffs and stimuli.[26]

[25] Results for households on the bi-monthly and monthly billing options are available on request from the authors.
[26] Results for this section are available from the authors on request.

7 Discussion, Summary and Conclusions

The analysis in this paper presents estimates of the response of a sample of Irish households to TOU tariffs and information stimuli in the residential electricity market. The quality of the data, along with the careful experimental design, allows us to examine these issues for the first time in Ireland. While the impact of TOU tariffs and information stimuli has been examined in other countries, the application to Ireland presents evidence for a country with a very different climate to that analysed in most recent analyses (i.e., a temperate climate with no household air conditioning).

Our results show that TOU tariffs and information stimuli are effective in influencing electricity consumption. In terms of information stimuli, the provision of an IHD is particularly significant. It must be noted that our results are not directly comparable with those of the statistical analysis of the data (Commission for Energy Regulation, 2011a). The statistical analysis involved a before-after analysis of electricity consumption under the different TOU tariffs and information stimuli. In addition, the researchers did not impose any parametric assumptions on the relationship between electricity consumption and prices/information stimuli and they imputed missing values for the cases in which electricity consumption readings were missing. Our analysis further controls for possible sources of heterogeneity across households (e.g., appliance ownership), and this allows us to separate out the pure effect of the variation in the tariffs and the presence of the stimuli from the environmental and household specific characteristics.

Our results are particularly interesting as they highlight how the presence of different TOU tariffs, in combination with different information stimuli, affects household electricity consumption during different times of the day. The results of different TOU tariffs indicate that TOU pricing is only statistically significant in influencing household electricity consumption during the peak period. This is not surprising given the sharp increases in peak period prices that were observed between the control and treatment periods, while the changes for the day and night periods were much smaller (see Table 1). However, we do observe a non-linear response to TOU tariffs for the peak period for households that received a bimonthly or monthly paper bill, in contrast to the results for households with an IHD where the response is linear. The magnitude of the results for monthly paper billing are closer to the results for the IHD stimulus, while the results for the bimonthly paper billing option are smaller in magnitude. This is consistent with the research noted above that stresses the importance of regular and easily understood feedback in influencing consumer energy use.

While there is a general tendency for peak usage to fall when TOU tariffs are in place regardless of information treatment, additional increases in the ratio of peak to night prices only results in limited further absolute decreases in usage. This could imply that while households understand that peak prices are higher under the new tariffs, but they do not fully understand how much higher they are under specific plans or that they have little scope to respond to higher prices beyond their initial reaction.

In order to understand how different groups react to the same changes in the TOU tariffs we split our sample in two, considering low and high education households separately. Our results show that, for the peak period, regular feedback in the form of an IHD is particularly effective in reducing peak-period electricity consumption, and the results also provide some evidence to suggest that this effect is stronger for low education households. The fact that high education households respond in a linear way to increasing peak prices is consistent with the research of Ito (2010) who suggests that individuals with higher education levels are better able to understand prices and information stimuli. However, the larger magnitude of the effects for low education households and the finding that these households shift electricity consumption towards the night period is suggestive of greater price sensitivity on the part of low education households, perhaps due to the correlation between education level and income. The fact that the latter effect is significant only for households with IHDs reinforces the importance of easily-understood, instantaneous feedback in influencing electricity consumption.

In the context of European climate policy targets and the importance of matching electricity supply and demand, these results have important policy implications. They indicate that TOU pricing can be effective in influencing peak period household electricity consumption, and suggest than the price response is more consistent when accompanied by real-time feedback in the form of an IHD. However, the weakness of responses to further relative price increases may suggest that the scope for demand response is quickly exhausted or that consumers use simple heuristics when considering how to respond. Further research will be needed to determine which of these mechanisms is most significant. The importance of appropriate information is again highlighted by the different results for households with low and high education levels.

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Appendix

Table 1: Control and Treatment Period Tariffs (€ cents per kWh, including VAT)

Tariff	Control Period	Treatment Period			*% change*		
	Peak, Day and Night	Peak	Day	Night	*Peak*	*Day*	*Night*
Control	16.24	16.00	16.00	16.00	*-1.5*	*-1.5*	*-1.5*
Tariff A	16.24	22.70	15.89	13.62	*39.8*	*-2.2*	*-16.1*
Tariff B	16.24	29.51	15.32	12.46	*81.7*	*-5.6*	*-23.1*
Tariff C	16.24	36.32	14.76	11.35	*123.7*	*-9.1*	*-30.1*
Tariff D	16.24	43.13	14.19	10.22	*165.6*	*-12.6*	*-37.1*
Tariff W/E	16.24	33.03	14.45	11.35	*103.4*	*-11.0*	*-30.1*

Note: The control and treatment period prices for the control group are slightly different as the control period electricity tariff was reduced (for all customers of Electric Ireland) in October 2009. The treatment period price for the control group therefore reflects the new lower tariff that was charged for all participants from October 2009 – December 2009, and for control group participants from January 2010.

Table 2: Number of Households involved in the Trial

Tariff Detail	Bimonthly	Monthly	IHD	Tot
Control Group	768	n/a	n/a	**768**
A	226	241	232	**699**
B	90	98	93	**281**
C	250	245	233	**728**
D	93	96	90	**279**
W/E	76	n/a	n/a	**76**
Tot	**1,503**	**680**	**648**	**2,831**

Source: Commission for Energy Regulation, 2011a.
Note: the weekend tariff was only combined with the bi-monthly billing information stimulus.

Table 3 Probit results

treatg	Coef.	Std. Err.
age group1	0.609	0.630
age group2	0.644	0.626
age group3	0.576	0.624
age group4	0.719	0.625
age group5	0.528	0.625
appliances	-0.082	0.059
high education	0.012	0.086
occupancy	0.055	0.072
income group	0.025	0.029
electric heating	0.021	0.150
_cons	0.036	0.651

***p<0.01, ** p<0.05, *p<0.1

Table 4: Estimation Results – Peak

	Bimonthly	Monthly	IHD
Tariff A	-0.0484**	-0.0509**	-0.0571***
	(0.0195)	(0.0209)	(0.0205)
Tariff B	-0.102**	-0.0848***	-0.0673**
	(0.0408)	(0.0244)	(0.0294)
Tariff C	-0.00777	-0.0818***	-0.0846***
	(0.0204)	(0.0239)	(0.0201)
Tariff D	-0.0625**	-0.160***	-0.102***
	(0.028)	(0.0325)	(0.0377)
Tariff W	-0.176***	-	-
	(0.0474)	-	-
Tp	-0.0435***	-0.0426***	-0.0430***
	(0.0098)	(0.0098)	(0.0098)
Tg	0.0421	0.0543	0.0552
	(0.0369)	(0.0369)	(0.0381)
DBankHoliday	-0.0276**	-0.0320***	-0.0189*
	(0.0115)	(0.0112)	(0.0112)
Sunday	-0.138***	-0.134***	-0.132***
	(0.0092)	(0.0092)	(0.0094)
Monday	0.00526	0.00735	0.00436
	(0.0054)	(0.0054)	(0.0052)
Tuesday	0.00988**	0.00750	0.00886*
	(0.0047)	(0.0049)	(0.0046)
Thursday	-0.0319***	-0.0402***	-0.0322***
	(0.0052)	(0.0056)	(0.0052)
Friday	-0.0760***	-0.0832***	-0.0769***
	(0.0063)	(0.0062)	(0.0065)
Saturday	-0.0821***	-0.0876***	-0.0806***
	(0.0088)	(0.0086)	(0.0091)
Sunshine	-0.0219***	-0.0217***	-0.0214***
	(0.0005)	(0.0005)	(0.0005)
HDD	0.0392***	0.0385***	0.0383***
	(0.0007)	(0.0008)	(0.0007)
ElectricHeating	-0.236***	-0.170**	-0.214***
	(0.0772)	(0.07)	(0.075)
HDDElecHeat	0.0121***	0.0118***	0.0151***
	(0.0039)	(0.0037)	(0.0037)
Appliances	0.208***	0.204***	0.191***
	(0.0282)	(0.0297)	(0.028)
Constant	-0.563***	-0.554***	-0.522***
	(0.0758)	(0.0798)	(0.075)
Observations	512,772	494,036	483,338

Standard errors in parenthesis, ***p<0.01, ** p<0.05, *p<0.1

Table 5: Estimation Results – Day

	Bimonthly	Monthly	IHD
Tariff A	-0.0130	-0.0260	0.00542
	(0.0165)	(0.0173)	(0.0186)
Tariff B	-0.0411	-0.0188	-0.00117
	(0.0358)	(0.023)	(0.024)
Tariff C	0.0300*	-0.0155	-0.00723
	(0.0156)	(0.0207)	(0.0163)
Tariff D	-0.00821	-0.0470*	-0.00705
	(0.0226)	(0.0255)	(0.0253)
Tariff W	-0.0765*	-	-
	(0.0418)	-	-
Tp	-0.0335***	-0.0325***	-0.0330***
	(0.0088)	(0.0088)	(0.0088)
Tg	0.0238	0.0361	0.0438
	(0.0319)	(0.0324)	(0.0326)
DBankHoliday	0.0888***	0.0769***	0.0814***
	(0.0082)	(0.0083)	(0.0084)
Sunday	0.0773***	0.0799***	0.0739***
	(0.0061)	(0.006)	(0.0065)
Monday	-0.00883***	-0.00386	-0.00741**
	(0.0033)	(0.0032)	(0.0031)
Tuesday	-0.000581	0.000725	0.00192
	(0.0027)	(0.0028)	(0.0027)
Thursday	-0.0187***	-0.0208***	-0.0172***
	(0.0028)	(0.0031)	(0.0029)
Friday	-0.0226***	-0.0272***	-0.0227***
	(0.0035)	(0.0036)	(0.0039)
Saturday	0.0540***	0.0522***	0.0479***
	(0.0056)	(0.0053)	(0.006)
Sunshine	-0.00986***	-0.00968***	-0.00960***
	(0.0003)	(0.0004)	(0.0004)
HDD	0.0224***	0.0215***	0.0218***
	(0.0006)	(0.0006)	(0.0006)
ElectricHeating	-0.190***	-0.114*	-0.127*
	(0.0718)	(0.0651)	(0.0649)
HDDElecHeat	0.0118***	0.0135***	0.0128***
	(0.0039)	(0.0034)	(0.0035)
Appliances	0.186***	0.174***	0.154***
	(0.0256)	(0.0267)	(0.0251)
Constant	-0.635***	-0.606***	-0.556***
	(0.0688)	(0.0717)	(0.0675)
Observations	513,165	494,377	483,578

Standard errors in parenthesis
***p<0.01, ** p<0.05, *p<0.1

Table 6: Estimation Results - Night

	Bimonthly	Monthly	IHD
Tariff A	0.0186	-0.00189	0.0316*
	(0.0163)	(0.0175)	(0.0177)
Tariff B	0.0102	0.0361	0.0303
	(0.0316)	(0.0266)	(0.0295)
Tariff C	0.0660***	0.0211	0.0382**
	(0.0175)	(0.0208)	(0.0182)
Tariff D	0.0450	0.0112	0.0388
	(0.0296)	(0.0298)	(0.0237)
Tariff W	-0.0419	-	-
	(0.0316)		
Tp	-0.0106	-0.00866	-0.00975
	(0.0089)	(0.0089)	(0.0089)
Tg	0.0549*	0.0682**	0.0668**
	(0.0318)	(0.0334)	(0.0337)
DBankHoliday	0.00776	-0.00244	0.00619
	(0.0066)	(0.0064)	(0.0066)
Sunday	-0.0418***	-0.0405***	-0.0407***
	(0.0048)	(0.0045)	(0.0047)
Monday	-0.0132***	-0.00983***	-0.00953***
	(0.0026)	(0.0026)	(0.0025)
Tuesday	-0.00193	-0.00107	-0.00134
	(0.0021)	(0.0018)	(0.0018)
Thursday	0.00418**	0.00357*	0.00463**
	(0.002)	(0.002)	(0.0019)
Friday	0.0244***	0.0190***	0.0224***
	(0.0026)	(0.0025)	(0.0027)
Saturday	-0.0176***	-0.0170***	-0.0178***
	(0.0044)	(0.0043)	(0.0044)
HDD	0.0110***	0.00956***	0.0103***
	(0.0007)	(0.0007)	(0.0007)
ElectricHeating	-0.233***	-0.150**	-0.194***
	(0.0692)	(0.0652)	(0.0651)
HDDElecHeat	0.0132***	0.0131***	0.0137***
	(0.0039)	(0.0035)	(0.004)
Appliances	0.0992***	0.0915***	0.0861***
	(0.0252)	(0.0278)	(0.0258)
Constant	-1.158***	-1.137***	-1.126***
	(0.0682)	(0.0746)	(0.0692)
Observations	512,853	494,200	483,355

Standard errors in parenthesis
***p<0.01, ** p<0.05, *p<0.1

Table 7: Estimation result – Education (high), IHD

	Peak	Day	Night
Tariff A	-0.0846***	-0.0172	0.00414
	(0.0296)	(0.0227)	(0.026)
Tariff B	-0.114**	-0.0492	-0.0159
	(0.0561)	(0.0496)	(0.0583)
Tariff C	-0.106***	-0.0233	0.00241
	(0.0292)	(0.0246)	(0.0274)
Tariff D	-0.0673	0.0192	0.0240
	(0.0630)	(0.0483)	(0.0447)
Tp	-0.0238	-0.0164	-0.00329
	(0.0178)	(0.0153)	(0.016)
Tg	0.0719	0.0482	0.0138
	(0.0659)	(0.0557)	(0.0568)
DBankHoliday	-0.0638***	0.0573***	-0.0303**
	(0.0213)	(0.0159)	(0.0121)
Sunday	-0.0814***	0.0929***	-0.0646***
	(0.0165)	(0.0117)	(0.0081)
Monday	0.0307***	-0.000661	-0.00923**
	(0.00892)	(0.00555)	(0.0044)
Tuesday	0.0188**	-0.00120	0.000606
	(0.00801)	(0.005)	(0.0031)
Thursday	-0.0321***	-0.0194***	0.00162
	(0.00870)	(0.0054)	(0.0035)
Friday	-0.0835***	-0.0282***	0.0124***
	(0.0106)	(0.0063)	(0.0042)
Saturday	-0.0820***	0.0457***	-0.0414***
	(0.0157)	(0.0114)	(0.0076)
Sunshine	-0.0230***	-0.0106***	-
	(0.000817)	(0.0006)	-
HDD	0.0394***	0.0224***	0.0122***
	(0.00118)	(0.0009)	(0.0011)
HDDElecHeat	0.0135*	0.0104	0.0137
	(0.00707)	(0.0084)	(0.0088)
Appliances	0.218***	0.177***	0.0771*
	(0.0507)	(0.0447)	(0.0439)
Constant	-0.611***	-0.596***	-0.988***
	(0.142)	(0.126)	(0.123)
Observations	173,393	173,506	173,333

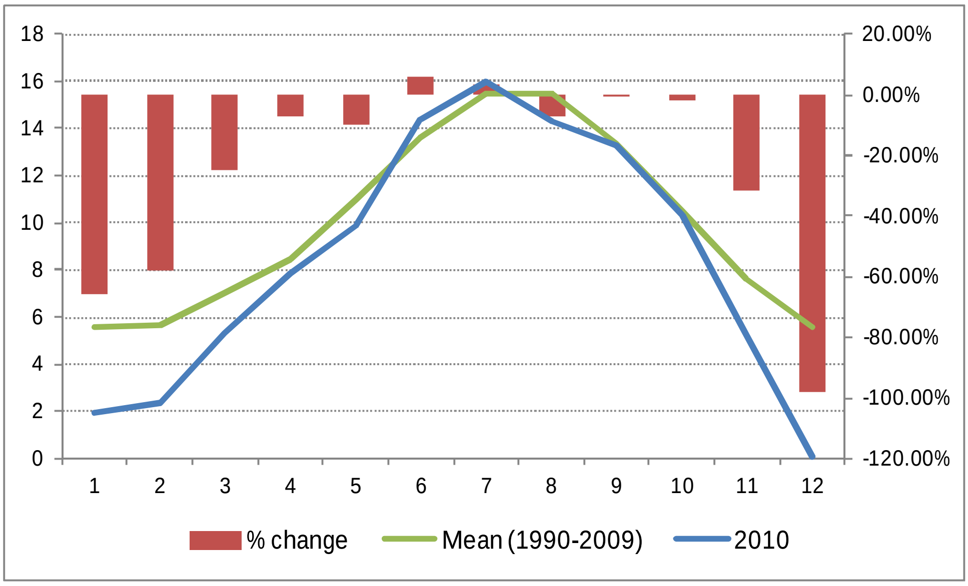
Standard errors in parenthesis
***p<0.01, ** p<0.05, *p<0.1
Results for bi-monthly and monthly billing are available from the authors upon request.

Table 8: Estimation results – Education (low), IHD

	Peak	Day	Night
Tariff A	-0.0410	0.0240	0.0527**
	(0.0302)	(0.0289)	(0.0259)
Tariff B	-0.0498	0.0267	0.0561*
	(0.0343)	(0.0247)	(0.0332)
Tariff C	-0.0828***	-0.00384	0.0596**
	(0.0275)	(0.0218)	(0.0248)
Tariff D	-0.125**	-0.0201	0.0559**
	(0.0492)	(0.0296)	(0.0269)
Tp	-0.0542***	-0.0459***	-0.0152
	(0.0123)	(0.0116)	(0.0115)
Tg	0.0730	0.0601	0.0908**
	(0.0486)	(0.0418)	(0.0435)
DBankHoliday	0.00585	0.0977***	0.0274***
	(0.0135)	(0.0103)	(0.0081)
Sunday	-0.160***	0.0618***	-0.0251***
	(0.0119)	(0.00834)	(0.0059)
Monday	-0.00637	-0.0130***	-0.00858***
	(0.0066)	(0.00382)	(0.0031)
Tuesday	0.00439	0.00216	-0.00222
	(0.0059)	(0.0033)	(0.0023)
Thursday	-0.0319***	-0.0172***	0.00703***
	(0.0068)	(0.0036)	(0.0024)
Friday	-0.0741***	-0.0208***	0.0293***
	(0.0088)	(0.0052)	(0.0037)
Saturday	-0.0834***	0.0483***	-0.00315
	(0.0114)	(0.0072)	(0.0056)
Sunshine	-0.0204***	-0.00881***	-
	(0.0007)	(0.0004)	-
HDD	0.0376***	0.0214***	0.00921***
	(0.0009)	(0.0008)	(0.0009)
HDDElecHeat	0.0158***	0.0146***	0.0144***
	(0.0043)	(0.0037)	(0.0044)
Appliances	0.184***	0.145***	0.0799**
	(0.0358)	(0.0324)	(0.034)
Constant	-0.529***	-0.567***	-1.200***
	(0.0933)	(0.085)	(0.0895)
Observations	278,881	278,998	278,948

Standard errors in parenthesis
***p<0.01, ** p<0.05, *p<0.1
Results for bi-monthly and monthly billing are available from the authors upon request.

Figure 1: Monthly temperatures, average (1990-2009) and 2010



Data source: Met Eireann, various years